

Cross-Cutting Ties, Organizational Density, and New Firm Formation
in the US Biotech Industry, 1994-1998

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Abstract

The present paper examines the role of cooperative relations among incumbents in the formation of new firms. We argue that cooperative interfirm relations that bridge geographically remote and diverse sources of knowledge, i.e., cross-cutting ties, contribute to new firm formation. Employing data on state-level entries in the US biotech industry from 1994 to 1998, we find support to the following hypotheses: the formation of new firms in a focal region of an industry is positively related to the number of cross-cutting ties; the number of cross-cutting ties negatively moderates the effects of organizational density on the formation of new firms.

INTRODUCTION

As White (2002: 286) observes, producers use their peers as benchmarks for adjusting their decisions. This view of competition is reflected well in the embeddedness hypothesis (Granovetter, 1985), which states that economic and social behaviors are facilitated and constrained by the set of social relations in which each market participant is embedded. A natural corollary of this hypothesis is that the pattern of interfirm relations surrounding organizations affects their economic exchanges and, more broadly, processes of competition (e.g., Baker, 1990; Burt, 1992; Gulati et al., 2000; Uzzi, 1997).

A widely accepted view in this regard is that cooperative interfirm relations positively affect firm performance by pooling resources and mitigating competition. Incumbents that do not participate in cooperative relations may be at a disadvantage compared with those embedded in them. Research on strategic alliances has repeatedly vindicated this view (Ahuja, 2000; Lavie, 2007; Powell et al., 1996; Rowley et al., 2000; Shipilov & Li, 2008). Hence, one important implication of the embeddedness hypothesis is that the firms embedded in cooperative relations outperform the third parties placed outside such relations.

While the embeddedness hypothesis is readily applied to incumbents in a given market, it remains unclear, however, whether or not the cooperation among incumbents poses a competitive threat to potential entrants, i.e., to the formation of new firms by nascent entrepreneurs. Of course, newly founded firms may perform better when they cooperate with incumbents because they are granted access to new resources (Baum, Calabrese, & Silverman, 2000; Stuart, Hoang, & Hybels, 1999). Yet, despite a few notable exceptions (i.e., Calabrese, Baum, & Silverman, 2000; Kogut, Walter, & Kim, 1995), not much is known about the effects of cooperation among incumbents on the potential entrants with no connections to incumbents.

Indeed, through interfirm cooperation, incumbents may pre-empt the resources otherwise available to nascent entrepreneurs, ultimately inhibiting their entry. In this study, however, we investigate one of the mechanisms through which cooperation among incumbents may be conducive to new firm formation. In particular, we contend that when cooperation among incumbents contributes to knowledge diversity, it will stimulate entrepreneurial activities and thus the formation of new firms. Our theoretical argument revolves around the notion of cross-cutting ties. Building on Simmel (1955) and Blau and Schwartz (1984), we define cross-cutting ties as those relations that provide access to geographically remote contacts beyond the focal firm's social boundary.

The structure of our argument is as follows. First, cooperative interfirm relations, such as R&D alliances, are a key conduit of knowledge creation (Hagedoorn, 1993, 2002; Rothaermel & Deeds, 2004). Second, spillovers undermine pre-emption; that is, the creation of new knowledge facilitates the formation of new firms as long as it spills over to nascent entrepreneurs (Acs et al., 2009; Audretsch & Stephan, 1999). Third, cross-cutting ties contribute to the transfer of new knowledge across regions, which in turn promotes new firm formation. Building on these considerations, we propose that in a given region of an industry, the number of cross-cutting ties positively affects the number of new firms founded and negatively moderates the effects of organizational density on the number of new firms. We test our hypotheses using the data on the state-level entries in the US biotech industry from 1994 to 1998.

THEORETICAL BACKGROUND

Scholars from economics and organization theory have long explored how *competition* underlies the evolution of an industry, i.e., the entry of new firms and the growth of incumbents. In contrast, the embeddedness hypothesis stresses that *cooperative* interfirm relations guide economic

exchanges and shape competitive outcomes (Baker, 1990; Granovetter, 1985; Uzzi, 1997). Mounting empirical evidence demonstrates the role of interfirm relations in determining firm performance (e.g., Baum et al., 2000; Shane & Cable, 2002; Gulati & Gargiulo, 1999).

The embeddedness hypothesis implicitly assumes that cooperative interfirm relations may pose a competitive threat to the firms not involved in such relations, particularly to nascent entrepreneurs. If incumbents appropriated all the resources on the market by cooperating with their rivals, new business opportunities would be depleted, and new firm formation inhibited. Yet, two empirical papers point to the opposite direction. Calabrese, Baum and Silverman (2000) argued that incumbents forming vertical alliances cannot entirely preempt the newly created knowledge because either spillovers or mimetic behaviors enable nascent entrepreneurs to benefit from the knowledge. Similarly, Kogut, Walter, and Kim (1995) observed that active cooperation among incumbents may signal the presence of emerging commercial or technological opportunities, which attract the attention of nascent entrepreneurs.

The crux of the debate lies in theorizing about the effects of two parties' cooperation on a third party not directly involved. We do not deny that the two parties involved in the cooperation seek to maximize the benefits stemming from it. Rather, we argue that the benefits of such cooperation may spill over to nearby entrepreneurs. As Owen-Smith and Powell (2004: 7) argued, interfirm relations are "leaky" pipelines that "function more like sprinklers, irrigating the broader community." Given the possible, unintended consequences of two parties' cooperation, theorizing about the effects of cooperation at the dyad level is rather myopic. In the present study, therefore, we address this issue by viewing cross-cutting ties as institutional channels for knowledge spillovers. Our arguments rely upon both geographical knowledge spillovers and the role of cross-cutting ties in triggering them.

Notice that we distinguish between resources and knowledge. Unlike resources, knowledge cannot be fully preempted – a phenomenon commonly understood as knowledge spillovers. Knowledge spillovers refer to positive externalities that third parties, not directly involved in the creation of the new knowledge, may benefit without paying its inventor (Arrow, 1962; Mansfield, 1985). Several empirical studies have suggested that knowledge spillovers stimulate entrepreneurial activities and lead to firm-level productivity increases in an industry or in a region (e.g., Audretsch, 1995; Audretsch & Feldman, 1996; Ceccagnoli, 2005).

The following two instances illustrate how spillovers may occur. First, the third party may discover new applications of the knowledge created by the inventor. Many entrepreneurs in the biotech industry were employees of large pharmaceutical firms and decided to start up their own business because they discovered business opportunities unexploited by their employers (e.g., Feldman, 2001; Kenney & Von Berg, 1999). Second, the third party may come to know what the inventor knows by recruiting staffs having previously worked for the inventor or by engaging in face-to-face interactions with the inventor. As Arrow (1962) argued, knowledge is non-excludable: once disclosed it is hard to exclude others from using it.

Notwithstanding a variety of channels for knowledge spillovers, such as cooperation with universities, formal alliance agreements, and labor mobility (Almeida & Kogut, 1999; Feldman, 2001; Owen-Smith & Powell, 2004; Stuart & Sorenson, 2003; Zucker et al., 1998), the common denominator to this literature is that the likelihood of knowledge spillovers increases with the number of actors involved in knowledge creation (e.g., Almeida & Kogut, 1999; Audretsch & Stephan, 1996; Owen-Smith & Powell, 2004). Compared with a single person's invention, knowledge creation by multiple parties results in more social contacts through which such knowledge may spill over to third parties. An interfirm relation (e.g., an alliance agreement) is a

primary example of this kind.

Among the various types of interfirm relations, we focus here on formal R&D cooperative agreements that involve firms from the same industry, yet located in different regions. As we will discuss below, such cooperation is likely to transfer new knowledge into the focal region. We refer to this type of cooperation as cross-cutting ties.

Scholars in sociology have long elaborated on the notion of cross-cutting ties. This concept, originally derived from Simmel's study on conflict (1955: 150-154) and further extended by Blau and Schwartz (1984), refers to the linkages that span across social categories or bounded groups. Cross-cutting ties help to connect different groups and provide them access to new information. In this regard, cross-cutting ties are out-category ties, as opposed to in-category ties (Wellman, 1988; McPherson Smith-Lovin, & Cook, 2001).

Cross-cutting ties are different from bridging ties that link otherwise isolated contacts (Burt, 1992). Unlike bridging ties that are defined on relational distance between contacts, cross-cutting ties are based on social distance between groups. These two notions however may converge when social distance comes to be similar to relational distance. One possible condition of this kind is the principle of homophily (McPherson et al., 2001), which states that actors proximate in the social space, such as same age or gender, are likely to connect to each other.

In parallel with Sorenson and Baum (2003), we embed our definition of cross-cutting ties into geography. In this study, cross-cutting ties are conceived of as relationships that link geographically dispersed groups, whose face-to-face interactions are infrequent. In particular, cross-cutting ties concern the social distance between groups with clear social boundaries, rather than the sheer physical distance between them. Accordingly, our approach echoes the definition of global structural hole developed by Reagans and McEvily (2001) and that of network range by

Reagans and McEvily (2003), both of which refer to ties that cut across institutional or social boundaries. Cross-cutting ties thus can be understood as ties that go “beyond a given social boundary” and connect separate knowledge sources.

Cross-Cutting Ties and Industry Evolution

The creation of new knowledge may stimulate business opportunities, which are essential for the evolution of an industry (Acs et al., 2009; Owen-Smith & Powell, 2004; Rothaermel & Deeds, 2004). As for the creation of new knowledge, the existing literature stresses the role of cooperative interfirm relations (Almeida & Kogut, 1999; Owen-Smith & Powell, 2004; Lavie, 2006). Obviously, the direct beneficiaries of cooperative interfirm relations are the incumbents that are embedded in those relations. Abundant empirical evidence supports this claim at the organizational level (e.g., Brass et al., 2004). Yet, the possible unintended consequences of cooperative interfirm relations for unspecified third parties call for an analysis beyond the organizational level. Drawing upon the literature of knowledge spillovers (Acs, Audretsch, & Feldman, 1992; Audretsch & Feldman, 1996; Audretsch & Lehman 2005; Feldman, 1994; Jaffe, Trajtenberg, & Henderson, 1993), we argue that the new knowledge created by cross-cutting ties may benefit the nascent entrepreneurs co-located in the same region.

The literature suggests that knowledge spillovers are geographically localized. This means that the firms located in the vicinity of an inventor may benefit without paying the costs of knowledge creation: what the innovator knows is likely to spill over to third parties co-located in the same region (Audretsch & Feldman, 1996; Jaffe et al., 1993). As Cooper and Folta (2000) have argued, knowledge spillovers may be more beneficial to emerging firms than to established ones. Therefore, to the extent that cross-cutting ties contribute to the transfer of new and diverse knowledge in a region, more entrepreneurial activities should emerge therein (see also Acs et al.,

2009). In particular, the following implications for new entrants are derived.

First, cross-cutting ties transfer new knowledge into a given region and thus increase the diversity of knowledge therein. Cross-cutting ties connect firms that operate in different geographical regions of an industry. Our assumption here is that the firms located in the same region are more likely to share similar knowledge than those that operate in different regions. That is because knowledge spillovers are localized in the vicinity of the knowledge created (Audretsch & Feldman, 1996; Jaffe et al., 1993; Singh, 2005). When firms develop cooperative relationships with partners located outside their region, they may access sources of unfamiliar knowledge, transferring this novel knowledge back into the region (e.g., Arikan, 2009). Indeed, Zaheer and George (2004) showed that in the biotech industry, alliances with partners located outside a firm's geographical locale guaranteed access to novel and diverse knowledge. Hence, the more cross-cutting ties in a given region of the industry, the more diverse knowledge is available within that region.

Second, the increase in knowledge diversity yields new business opportunities for nascent entrepreneurs. The entrepreneurship literature (e.g., Shane, 2001; Thornton, 1999) suggests that new business opportunities increase as the technical and commercial knowledge accessible to nascent entrepreneurs becomes more abundant. Entrepreneurship is often conceived of as a process of tapping into the opportunities generated by knowledge spillovers (Acs et al., 2009; Audretsch, 1995; Audretsch & Lehmann, 2005). By channelling new knowledge into the region, cross-cutting ties serve to create new business opportunities not fully pre-empted by incumbents. For example, knowledge diversity leads to product variety as it enhances the room for discovering new ways of production (Fleming, 2001; Fleming & Sorenson, 2001), and has been found to attract new entrants and to foster innovation in a region (Jacobs, 1969; Glaeser et al.,

1992). Hence, the diversity of knowledge created by cross-cutting ties should facilitate the exploitation of new business opportunities by nascent entrepreneurs.

Hypothesis 1: The number of new firms in a given region of an industry will increase with the number of cross-cutting ties in that region.

Cross-Cutting Ties and Organizational Density

As cross-cutting ties contribute to the diversity of knowledge in a region, the level of competition therein may be affected as well. In particular, the increase in knowledge diversity enabled by cross-cutting ties should lower competitive intensity. For example, when knowledge diversity frees new business opportunities, specialist firms proliferate and face less competition (for a similar logic see Carroll, 1985). In this respect, the effects of cross-cutting ties on new firms may have implications for density-dependence as well (Carroll & Hannan, 2000).

The density dependent process is described as follows. When a limited number of firms develop an emerging business, customers and suppliers are not familiar with it and are reluctant to engage in economic exchanges with those firms. Nonetheless, increases in organizational density – commonly defined as the number of firms (Carroll & Hannan, 2000) – augment the social recognition of this business, and attract more entrepreneurs to it. However, further increases in organizational density intensify the competition among those firms because they compete for the same pool of increasingly scarce resources. As a consequence, the number of new firms founded exhibits an inverted U-shaped relationship with the density of firms in the business (Hannan & Freeman, 1989; Carroll & Hannan, 2000).

The assumption behind the effects of density-dependence is that the firms involved in a given business are identical; they adopt comparable structures, business models, and compete in a

market of undifferentiated products (Carroll & Hannan, 2000). In what follows, we argue that the effects of organizational density are not independent from those of cross-cutting ties because such interfirm relations influence the diversity of knowledge in a region and, potentially, that of the businesses located therein. In particular, we argue that cross-cutting ties counter-balance the effects of density-dependent legitimation and competition.

First, legitimation is hampered by cross-cutting ties as such relations lead to the emergence of different products and firms. As McKendrick and Carroll (2001: 661) put it, “the diversity of ... those organizations operating in this market work against the institutionalization of disk array (firms)”. The existence of multiple types of firms yields confusion in the eyes of stakeholders and market participants, tarnishing the legitimation of the business. As McKendrick and his colleagues (2003) have shown, the emergence of homogeneous producers is a critical precondition for the birth of a new business. Similar findings are also reported by Boone and his collaborators (2007). With respect to legitimation, the effects of organizational density are negatively moderated by the number of cross-cutting ties in a given region.

Second, the diversity of knowledge stimulated by cross-cutting ties lowers the competitive effects associated with high organizational density. Suppose two different regions, one marked by high organizational density and the other by low organizational density. The theory of density dependence suggests that the level of competition would be more intense in the former case (Hannan & Freeman, 1989). However, our argument suggests that cross-cutting ties contribute to reducing the intensity of density-dependent competition even in presence of overcrowding, i.e., in the first region. That is because the diversity of knowledge available in a region underlies a diversity of market niches and business models, thereby reducing the competition for resources.

Hypothesis 2: The inverted-U shaped effect of organizational density on the number of new firms in a given region of an industry will be negatively moderated by the number of cross-cutting ties in that region.

METHODS

Biotechnology Industry

We tested our hypotheses using data on the U.S. biotechnology industry during the period 1994 to 1998. Cooperative interfirm relations or strategic alliances, such as co-development of drugs or their co-promotion, have been considered critical to firm performance in this industry (Baum et al., 2000; Hagedoorn, 1993, 2002; Powell et al., 1996). New product development is a risky and capital-intensive process that encompasses drug discovery, clinical tests, and large-scale manufacturing and distribution. As most of the biotechnology firms are small, specialized (e.g., Arora et al., 2001), they have limited resources and technologies and enter into alliances to minimize developmental risks and the associated costs. Such alliances offer access to new compounds and technologies and reduce the time to market products (Rothaermel & Deeds, 2004; Shan et al., 1994; Stuart et al., 1999). The number of R&D alliances in this industry increased substantially during the time period of this study. Similarly, the growth rate of patents granted increased after 1994 and peaked in 1996. Thus, the role of strategic alliances made this industry appropriate for an empirical examination of cross-cutting ties.

Biotechnology refers to “techniques that use organisms or their cellular, subcellular, or molecular components to make products or modify plants, animals, and micro-organisms to carry desired traits” (Paugh & LaFrance, 1997). So far, little consensus has been achieved regarding the boundary of the biotechnology industry. Because the biotechnology industry is defined on the basis of technologies rather than final products, its boundary is not easily and clearly

distinguishable. Conceptually, it would be relevant to include any product that incorporates biotechnology as a part of the industry. Such an approach, however, expands the boundaries of the industry almost infinitely and renders empirical research difficult. It is because most empirical data are structured based on the SIC (Standard Industrial Classification) or NAICS (North American Industry Classification System) codes, which in turn are based on final products of each industry, and not technologies underlying those products. To resolve this boundary issue, the present study defines the biotech industry with an emphasis on diagnostics and therapeutics, which account for more than 90 percent of biotechnology-related revenues (Standard & Poors, 2000). While our definition is rather conservative, it covers the lion share of biotechnology-related revenues and, more importantly, makes empirical analysis manageable.

Dependent Variable: Number of new firms

The number of new firms was measured by the number of *de novo* entries in the biotechnology industry in a given state. A *de novo* entry for year T is defined as an active business entity that hires at least one employee and that did not exist prior to year T (e.g., Luger & Koo, 2005). This definition excludes both a new business entity that is a branch of multi-establishment firms and one that is created by name or location changes. Data on *de novo* entries were obtained from the Longitudinal Establishment and Enterprise Microdata (LEEM) archive.

Explanatory Variables

Cross-cutting ties. We measured the number of cross-cutting ties in a given state as the number of R&D agreements between firms located in the focal state and those in other states. For year T , this variable includes only cross-cutting ties involving incumbent firms – i.e., firms founded at least in year $T-1$. Information on R&D agreements in this industry was obtained from the Recombinant Capital database. In total, 621 cross-cutting ties were observed during the five

years of our observation period, 17 of which involved new firms. The remaining 604 cases were employed to compute this variable. The number of cross-cutting ties varied from a low of 96 in 1994 to a high of 168 in 1997.

Because our study concerns cooperation among incumbent firms, we did not examine industry-university linkages and personnel mobility. Moreover, we did not regard as cross-cutting ties marketing agreements, such as joint promotion campaigns, which did not involve intensive transfer of knowledge between partners. We also excluded R&D agreements that targeted markets outside the U.S.: such alliances were unlikely to directly benefit U.S. entrepreneurs. In doing so, we limit our attention to the R&D agreements whose primary goal was to access the technologies and the R&D capabilities of partner firms. The geographical distribution of R&D agreements observed during our study period suggests that the alliances connecting firms belonging to different states represent a suitable operationalization of cross-cutting ties, i.e., ties that link knowledge sources with distinct boundaries. The reasons of this claim are as follows.

First, the lack of uniform nation-wide regulations represents an important obstacle to the development of the biotech industry. Depending on laws regulating biotech products, firms will decide what to develop and how to develop their products. Biotechnology in the United States was regulated by at least five U.S. federal agencies: the Environmental Protection Agency (EPA), U.S. Department of Agriculture (USDA), National Institutes of Health (NIH), the Occupational Safety and Health Administration (OSHA) and the Food and Drug Administration (FDA). None of these agencies was in charge of overseeing all the methods and products of biotechnology. Instead, the White House Office on Environmental Policy coordinated the efforts of the separate agencies. Accordingly, legal and administrative infrastructures varied substantially across biotech product segments and the existence of state-specific legislation led firms in different states to

vary with respect to the type of R&D investments.¹

Second, insofar as an alliance is a vehicle to access knowledge otherwise not available, frequent alliances between two sources may indicate that the knowledge of two sources differs. The database of Recombinant Capital yielded 621 R&D agreements among firms from different U.S. states between 1994 and 1998, but also 138 R&D agreements among firms located in the same state. The number of within-state R&D agreements observed was approximately one fourth of the between-state R&D agreements. A majority of within-state R&D agreements were concentrated in states with a larger number of between-state agreements. We interpret this distribution of alliances as suggesting that the quest for new knowledge of biotech firms is better fulfilled through between-state rather than within-state cooperative agreements.

Lastly, the developmental stage of the biotech industry varied significantly across states. Owing to its strong science base, the biotech industry customarily flourished in those locations where major research universities or institutes were located. In addition, the biotech firms located in each state could not develop their R&D strengths in all the sub-segments of the industry. For instance, firms in California specialized in medical devices and equipment, but were not as competitive in the drug and pharmaceutical sector as their counterparts in North Carolina or Pennsylvania (Biotech Industry Organization, 2006). Although an increasing number of states invested millions of dollars to support bioscience, there were still significant variations in the depth and breadth of knowledge across states (e.g., Feldman, 2003).

Our analysis of patents and patent classes supports this claim. For each state, we created a vector of patent classes in the rank order of the number of patents. We then computed pair-wise Spearman's rank correlations across different states. If the rank correlation is one, it indicates that

¹ Biotech firms in California were exempt from the 6 % state sales tax; those in North Carolina were exempt from a tax on the purchase of manufacturing equipments (Lord Sainsbury, 1999, Biotechnology Clusters, DTI, UK).

the frequency distribution of patent class is identical across different states. Any value distant from one suggests that the distributions are not identical, i.e., states differ with respect to knowledge. The average Spearman's correlation for each state varied from -0.355 to 0.663. The correlation for California, Massachusetts, and North Carolina were 0.558, 0.615, and 0.469, respectively. The distribution of the correlations suggests, in accordance with Feldman (2003), that there existed regional specialization in biotech-related knowledge.

Organizational density. As routinely done in the organizational ecology literature (e.g., Carroll & Hannan, 2000), organizational density, a proxy for density-dependent legitimation and competition, was measured by the number of firms that operated in a given state. To correct for skewness and mitigate correlations with other control variables, we log-transformed this variable (Hannan & Freeman, 1989). Information to compute this variable was obtained from LEEM as well as the Census Business Patterns, both of which were compiled by the U.S. Census Bureau.² Hypothesis 2 was tested by including an interaction term between the cross-cutting ties variable and the linear and squared measure of organizational density. The coefficients of these interactions will indicate whether the effects of cross-cutting ties strengthened or suppressed those of density dependent legitimation and competition, i.e., the inverted U-shaped effect of organizational density on the number of new entries (Hannan & Freeman, 1989).

Control Variables

Our key assumption is that the knowledge created through cross-cutting ties is available to nascent entrepreneurs. However, three sets of alternative explanations may be at work. First, the effects of cross-cutting ties could be confounded with the structure of interfirm relations, in particular, the degree of non-redundant contacts. As widely discussed in the network literature,

² Alternatively, one may use Dun and Bradstreet database, yet the nationwide organizational density shows a big fluctuation in the 90s, a pattern that is not found in other nation-level statistics. Hence, we opted for the Census Bureau data as we considered them more reliable.

the structure of interfirm relations affects the nature of the knowledge created, which is ultimately available to nascent entrepreneurs. To control for the effects of tie structure, we included Burt's (1992) measure of *network constraint*. This measure reflects the extent to which a given region is connected to other regions that are mutually connected.

Second, besides cross-cutting ties, other channels of knowledge spillovers may benefit nascent entrepreneurs. One important source of spillovers documented by regional economists is the research carried out by universities. To control for this possibility, we constructed the *sum of university R&D spending*, which is the total sum of R&D spending by local universities, obtained from the National Science Foundation (NSF). To normalize this variable and allow across-states comparisons, we divided it by the national annual mean. Hence, a value of one indicates that the R&D spending of a given state equals the national average in a given year. Moreover, when start-ups enter a region by forming alliances directly with incumbents, they may directly access the relevant knowledge rather than indirectly benefit from knowledge spillovers. To control for such an effect, we constructed a variable, *ties involving new firms*, which counts the number of alliances held by new firms in the focal state at the time of their entry.

Lastly, the regional economics literature has long recognized the availability of resources as a key driver of new entries in a region (Acs et al., 2009; Audretsch & Lehmann, 2005; Feldman, 2001). A region with more cross-cutting ties may abound with resources and opportunities, both of which underlie new entries. To further control for this alternative explanation, we included the following two variables: *the number of science and engineering department (S & E depart.) graduates* in a given state – a proxy for the supply of quality labor – and *venture capital per density*, i.e., the amount of equity investments made by venture capitalists in the focal state. The latter was based on data from the Thompson Financial, whereas the data

concerning the former were obtained from the IPEDS report of the National Center for Education Statistics. As in the case of university R&D spending, we normalized the values concerning the number of S&E department graduates. As for the venture capital per density variable, to underscore the relative magnitude of investments to incumbent organizations, we divided the amount of venture capitalists' investments in the focal state by the number of ventures that received investments from venture capitalists.

Model Specification

We assumed that the number of *de novo* entries in each state followed a Poisson distribution. Yet, this assumption may not hold true when overdispersion is present. Although parameter estimates remain unbiased in the presence of overdispersion, they are inefficient and their standard errors are biased downward (Long, 1997). Wald test for overdispersion failed to reject the null hypothesis at the 0.05 significance level.³ This result suggested that a Poisson model might be appropriate for our data. Accordingly, the expected number of new firms in state i in year t , λ_{it} , is specified in the following way:

$$\lambda_{it} = \kappa_t \exp[\beta_0 + \beta_1 BT_{it} + \beta_2 OD_{it} + \beta_3 OD^2 + \beta_4 (BT \times OD) + \beta_5 (BT \times OD^2) + \beta \Lambda_{it} + e_{it}]$$

where κ_t is year fixed effects, CT is the number of cross-cutting ties, OD is organizational density, Λ_{it} is the set of control variables, and the unit of analysis of the present study is each state in the U.S. biotechnology industry.

Insert Table 1 about here

It is possible that unobserved heterogeneity at the state level may arise from unspecified attributes of each state. To cope with this concern, we employed an unconditional fixed effects

³ The likelihood ratio test also failed to reject the null hypothesis at 0.01 significance level.

model when estimating the effects of the covariates on the dependent variable. Moreover, we included year dummies to control for unspecified temporal variations that were constant during a given year. The maximum likelihood method was employed to estimate the parameters. SAS version 8 was used to fit the model to the data. Table 1 presents the descriptive statistics of the covariates included in our models.

RESULTS

Figure 1 shows the age distribution of cross-cutting ties, the key variable of interest in this study. The age of a cross-cutting tie is defined as that of the younger firm involved in the alliance. The age of zero indicates that a new firm participated in the alliance as a partner. Ties involving new firms, one of our control variables, refers to the number of ties with zero age. For 17 cases out of 621 cross-cutting ties, the age of a tie turned out to be zero. This indicates that cross-cutting ties involving new firms are rather infrequent.

Insert Figure 1 about here

Table 2 shows the estimates of the number of new firms in the U.S. biotechnology industry from 1994 to 1998. Due to missing values, the state of Hawaii was excluded, which resulted in the inclusion of a total of 49 states. Model 1 includes only control variables and serves as a benchmark for the three different models that are derived from our theory. As for the control variables, Model 1 shows that the R&D spending of local universities is positively related to the number of new firms. The estimates for organizational density reveal the inverted U-shaped pattern, widely demonstrated in the literature: while the initial growth in density stimulates new entries, further increases tend to suppress them because of heightened competition.

Insert Table 2 about here

In Model 2, we examine whether cooperative relations exhibit any effect on the formation of new firms. Consistent with Hypothesis 1, the estimates of cross-cutting ties in Model 2 show a positive and statistically significant direct effect, even when we control for organizational density and the carrying capacity of the environment. The effect of cross-cutting ties, CT , exhibits the following form: $0.476CT - 0.148OD*CT + 0.011OD^2*CT$. The first order derivative of this

equation with respect to the cross-cutting ties variable is $\frac{\partial Y}{\partial x} = \exp[g(x)]g'(x)$ where x is the number of cross-cutting ties and $g'(x) = 0.476 - 0.148*OD + 0.011*OD^2$. For instance, at the mean value of organizational density (i.e., $OD = 4.49$), the first order effect of cross-cutting ties equals 1.024 in Massachusetts in 1998 when other covariates are set to their sample mean.⁴ This result indicates that cross-cutting ties contribute to expanding business opportunities available to nascent entrepreneurs, ultimately increasing the number of new firms in a given state. To examine whether these effects are robust to alternative functional forms, we re-run a model employing the logged number of cross-cutting ties. The results obtained are consistent with those reported in Model 2.

Consistent with Hypothesis 2, the interaction of cross-cutting ties and the first-order effect of density is negative, whereas that of cross-cutting ties and the squared term of density is positive. This pattern suggests that the density dependent processes of legitimation and competition are negatively moderated by the number of cross-cutting ties in a given state. To illustrate this result, we plot the interaction in Figure 2. This figure benchmarks the curvilinear effect of density in the absence of cross-cutting ties with the effect in presence of cross-cutting ties at their sample mean. While the effect of density-dependent legitimation and competition

⁴ For the full range of the OD variable, the main effects (see Aiken & West, 1991) of cross-cutting ties are positive.

appears evident in the absence of cross-cutting ties, the increase in cooperative relations among incumbent firms belonging to different states negatively moderates both these processes.

Insert Figure 2 about here

Robustness Checks

We undertook several additional analyses to prove the robustness of our results to measurement issues and to alternative methods of estimation.⁵

Endogeneity & resource availability. We address the potential endogeneity of cross-cutting ties in Model 4 of Table 2. As a region with abundant resources is more likely to exhibit cross-cutting ties and new firms are more likely to enter into it, our estimates of cross-cutting ties may be confounded with the effects of resource availability in the focal region. While our control variables may minimize this potential endogeneity in the estimation, we further control for this possibility by employing an instrumental variable (IV) estimation of our count model, as suggested by Mullahy (1997). Cross-cutting ties are instrumented by the number of inhabitants in a state and venture capital per density. The partial F test statistic against Model 1 is 7.1 with a p -value of 0.06, showing that IV estimates do not provide a better fit to the data compared with Model 2. Moreover, the results of Model 4 are consistent with those reported in Model 2. This suggests that the estimates for cross-cutting ties in Model 2 are unlikely to be spurious.

Insert Table 3 about here

Between-state variation in carrying capacity. Our fixed effects ML estimates examine the effects of cross-cutting ties in a given state on the number of new entries in that region.

⁵ As it is likely that knowledge takes time to spill over to nascent entrepreneurs, we also explored the lagged effects of cross-cutting ties by re-estimating Model 2 with one-year lagged covariates. As Model 3 shows, the results remain similar to those of Model 2. It suggests that the contemporaneous effect of cross-cutting ties is weaker than that of its lagged counterpart.

Accordingly, differences across regions should not influence our estimation, which utilizes within-state variation only. Note also that for the sake of comparability with extant ecological research, we measured density as the sheer number of firms operating in a given state. Nonetheless, the estimates of organizational density may be contingent upon the carrying capacity of the focal state. Although several controls were included in our models⁶, we undertook additional analyses in which we divided the measure of organizational density by the number of inhabitants in the focal state, a proxy for the size of demand and labor supply. Model 1 of Table 3 reports results consistent with those discussed so far.

Knowledge spillovers. Our main analysis did not take the content of R&D agreements into account. Nonetheless, the specific contents of R&D agreements may lead to variations in the effects of cross-cutting ties. To uncover this, we classified R&D agreements into two categories: with and without technological licensing agreements. We expect that the size of knowledge spillovers is larger for the alliances with technological licensing because licensing involves codification and codified knowledge is more prone to spill over. The results reported in Models 2 and 3 of Table 3 confirm this expectation. Those with licensing agreements exhibit significant positive effects on new entries in a given state ($\beta_1 = 0.840$ in Model 2), whereas those without licensing agreements do not display significant effects.

While knowledge spillovers are found to be present at the state level (Anselin, Varga, & Acs, 1997; Jaffe et al., 1993), not all the actors in a given state are the equal beneficiaries of knowledge spillovers. To examine this possibility, we conducted a further analysis at the MSA (metropolitan statistical area) level by assuming that the actors located in a MSA with active biotech activities are more likely to benefit from spillovers. We selected 46 MSAs whose drug-

⁶ The number of within state ties may also reflect resource abundance in a region. Even when this measure is included, the results obtained remain similar to those reported in Model 2 of Table 2.

related patents were above the national annual average. Then, we pooled multiple MSAs in the same state into one cluster if they were closely connected via multiple within-state R&D agreements. In doing so, we used within-state ties to judge the degree of cohesion at the state level. As a result, we obtained 20 MSAs and 7 combined MSAs or clusters.⁷ Model 4 of Table 4 reports the estimates obtained from the MSA-level models. The patterns appear largely consistent yet we obtain statistically significant results only when employing technology licensing agreements as cross-cutting ties, and not logging the organizational density variable. We interpret this finding as suggesting that the detection of the effects of cross-cutting ties remains contingent on the proper specification of the effects of density-dependence.

Insert Table 4 about here

Our hypotheses presume that by transferring new knowledge across states, cross-cutting ties may increase the knowledge diversity of a given state. To explore this assumption, we employed patent-citation data from the U.S. Patent and Trademark Office and constructed the following two diversity measures: knowledge diversity and complementarity-adjusted knowledge

diversity. First, knowledge diversity (KD) is defined as: $KD_{jt} = 1 - \sum_{k \in M} \left(\frac{p_{kjt}}{p_{\bullet jt}} \right)^2$ where M is the

set of SIC-corresponding patent classes, and p_{kjt} and $p_{\bullet jt}$ are the number of patents in SIC-corresponding class k in state j and the total number of patents in state j , respectively, in year t .

Knowledge diversity is assumed to be low when the majority of patents are granted in a certain SIC-corresponding patent class. Second, complementarity-adjusted knowledge diversity (KDC) is

⁷ They include California (i.e., San Francisco, Oakland, San Jose, Los Angeles, Orange County, and San Diego), Texas (i.e., Austin, Dallas, Houston, and San Antonio), Ohio (i.e., Cincinnati, Cleveland, and Columbus), New Jersey (i.e., Bergen, Middlesex, Newark, and Trenton), Connecticut (i.e., Hartford, New Haven, and New London), New York (i.e., Albany, Nassau, New York, and Rochester), and Pennsylvania (i.e., Philadelphia and Pittsburgh).

defined as: $KDC_{jt} = KD_{jt} \times \sum_{k \in M} w_k q_{kjt}$ where M is the set of SIC-corresponding patent classes, w_k is a share of the contribution made by SIC-corresponding class k to patents in the field of biotechnology industry, and q_{kj} is the proportion of patents from SIC-corresponding class k in state j in year t . This measure reflects the extent to which the knowledge available in a specific state is diverse and at the same time complementary. Knowledge in a region is complementary as it is easily synthesized for the development of new inventions. A higher value of this measure indicates that knowledge available in a state is not only diverse but also complementary, i.e., easy to recombine and thus likely to result in new inventions.

Because the measure of knowledge diversity ranges between 0 and 1, we employed a double censored Tobit model to investigate the relationship between knowledge diversity and cross-cutting ties. Knowledge diversity is the byproduct of the knowledge creation efforts in a focal state. Therefore, in the models reported in Table 4, we included the following covariates that may proxy knowledge creation efforts: the sum of university R&D spending, venture capital per density, the number of S&E graduates, and organizational density (e.g., Cohen & Klepper, 1992). While the fit of the model to the data is higher in Model 2 than in Model 1, the estimates of cross-cutting ties appear robust across the two models. The positive and statistically significant coefficient estimates of the cross-cutting ties variable are consistent with our assumption: the more cross-cutting ties that are present in the focal state, the more diverse is the knowledge available in that state.

CONCLUSION AND DISCUSSION

The present study examines the role of interfirm relations among incumbents in new firm formation. More specifically, we focus on alliance agreements among firms in the same industry,

yet located in different institutional and geographical contexts. We view such cooperation as a key conduit for new knowledge transfer and a facilitator of new entries. Our model draws on the literature on knowledge spillovers (Acs et al., 2009; Audretsch, 1995; Audretsch & Lehmann, 2005) and contend that cross-cutting ties stimulate new firm formation by expanding the knowledge available to potential entrepreneurs. We tested our model by using the data on the US biotech industry from 1994 to 1998. The results obtained – which proved to be robust across a wide variety of specifications – suggest that (i) cross-cutting ties are positively related to the number of new firms observed in a given state and (ii) negatively moderate density-dependent processes of legitimization and competition.

From a theoretical standpoint, this paper shows that the effects of interfirm relations are not limited to the firms embedded in those relations, but extend to third parties as well. Despite many empirical studies on the embeddedness hypothesis, an analysis of the industry-level outcomes, not the organizational-level ones, is rare except for small-world network studies (e.g., Baum, Shipilov, & Rowley, 2003; Powell et al., 2005). In particular, the current literature mainly focuses on the effects of social relations on the parties directly embedded in them, but remains largely ignorant of their unintended consequences for those that do not enter such relations. This study draws the attention to nascent entrepreneurs as third parties not embedded into such relations. As the liability of newness suggests, nascent entrepreneurs hardly prevail over incumbents when incumbents pre-empt key resources. However, this study shows that unlike resources, knowledge cannot be fully pre-empted and that knowledge spillovers may enable nascent entrepreneurs to discover and pursue new business opportunities.

Moreover, the present paper views formal interfirm relations as a key trigger for regional knowledge spillovers. The entrepreneurship literature emphasizes the role of individual and

institutional ties as channels of knowledge spillovers, which fuel entrepreneurial activities. Most studies focus on linking non-commercial institutional ties, such as university-to-scientist ties, to entrepreneurial activities. Inspired by the work of Mansfield (1983), the present study however suggests that commercial ties, such as R&D agreements among profit-seeking firms, may also serve as a channel for knowledge spillovers. Obviously, formal agreements *per se* do not necessarily engender regional knowledge spillovers. Rather, the direct consequence of formal R&D agreements is the transfer of new knowledge. However, such knowledge has the potential to spill over to the third parties – both nascent entrepreneurs and other incumbents that are co-located with the firms entering such agreements. That is because co-location facilitates frequent face-to-face interactions or individual ties, the crucial vehicles for knowledge spillovers.

This paper also contributes to clarifying a possible boundary condition of density dependence (for a review see Carroll & Hannan, 2000). In particular, our results indicate that the evolution of organizational populations is influenced not only by organizational density but also by the intensity of cross-cutting ties in an industry. Without the careful examination of cooperative interfirm relations, density-dependent process would provide only a partial view of industry evolution. While it is now clear that organizational diversity reduces competition (e.g., Baum & Mezias, 1992), the literature has only recently started to explore the role of organizational diversity in the emergence of a new business (e.g., McKendrick et al., 2003; Boone et al., 2007). The present paper provides a fresh perspective on this issue. Similarly to the legitimacy discounts encountered by the organizations involved in different businesses (McKendrick et al., 2003), our model suggests that horizontal relations among incumbent firms from different institutional contexts may hamper the legitimation process. To the extent that legitimation is a matter of cognitive categorization (Hannan et al., 2007), our findings suggest

that knowledge diversity fostered by cross-cutting ties may inhibit the development of a crisp consensus concerning the defining properties of a new business.

Moreover, our analysis of cross-cutting ties has implications for the study of exploration and exploitation alliances (e.g., Beckman, Haunschild, & Phillips, 2004; Lavie & Rosenkopf, 2006; Rothaermel & Deeds, 2004). This line of research focuses on the conditions under which exploration alliances are preferred to exploitation ones, and on their associated performance gains. Cross-cutting ties may be conceived of as an instance of exploration alliances because they allow firms to access new knowledge. If so, our analysis implies that incumbents would risk facing more competition when actively engaging in exploration alliances. The reason is that the knowledge diversity induced by cross-cutting ties provides new business opportunities to potential entrants as well as to incumbents. Hence, cross-cutting ties that are supposed to primarily help incumbents may trigger new entrants as well. The mechanism underlying this effect lies in the knowledge spillovers created by cross-cutting ties. Our narrative appears aligned with that of Teece (1986) who suggested that the returns to the creation of new knowledge are not necessarily appropriated by its direct contributor. In this regard, it would be interesting to examine the competitive effects of cross-cutting ties on the performance of the incumbent firms embedded in such relations. For example, when incumbents suffer from structural inertia and core rigidities (Hannan & Freeman, 1989; Leonard-Barton, 1992), knowledge spillovers should help nascent entrepreneurs to compete with them more effectively.

On a managerial standpoint, our study implies that when locating operations, nascent entrepreneurs should take the potential for knowledge spillovers into account. Typically, entry decisions are based on the evaluation of industry attractiveness, such as competitive intensity and the availability of reliable suppliers. The positive direct effect of cross-cutting ties suggests that a

region with active knowledge creation may offer rich business opportunities to nascent entrepreneurs. The number of cross-cutting ties as well as the R&D spending of nearby research institutions is a good indicator of knowledge creation and, eventually, of business opportunities. Our results also suggest that new entrepreneurs should consider entering cross-cutting ties when density is low because the positive direct effect of cross-cutting ties outweighs the negative effects of the interaction between cross-cutting ties and organizational density. Conversely, cross-cutting ties are more favourable to incumbents when accompanied by density increases.⁸ For policy makers, our results indicate that in a region marked by a large number of firms (i.e., when density dependent competition is at work), governmental agencies may consider supporting inter-firm cooperative agreements that bridge distant sources of knowledge as they may serve to weaken the negative effects of organizational density on new entries.⁹

Despite these implications, our study presents several limitations as well. First, our findings may be industry-specific. When firms in an industry opt for mature technologies and do not differ from one another, the quest for alliances may decrease and the effects of cross-cutting ties may not be substantial. Second, informal social relations that span distant sources could also be a conduit of knowledge spillovers and thus a potential alternative to cross-cutting ties. The literature, as well as qualitative evidence on the biotech industry, suggests that entrepreneurial activities are often regionally bounded and the development of the biotech industry appears uneven in the US. This leads us to assume that cross-cutting ties provide access to diverse knowledge. Yet, informal social relations may offer alternative access to proprietary knowledge too. For example, spillovers may exist when scientists interact on various commercial projects

⁸ When we log-transform the model to make our interpretation simpler, the marginal effect of cross-cutting ties (i.e., *CT*) contingent upon the level of organizational density (i.e., *OD*) is following:

$$\partial \log \lambda / \partial CT = 0.476 - 0.148 \times OD + 0.011 \times OD^2$$

⁹ We are indebted to an anonymous reviewer for his/ her valuable suggestions on this matter.

across different geographical areas. Indeed, in our study, the effects of formal R&D agreements could materialize through informal relations. A direct comparison of such formal and informal channels of knowledge spillovers needs to be undertaken to test the robustness of our findings.

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FIGURE 1. The Age-Frequency Distribution of Cross-Cutting Ties

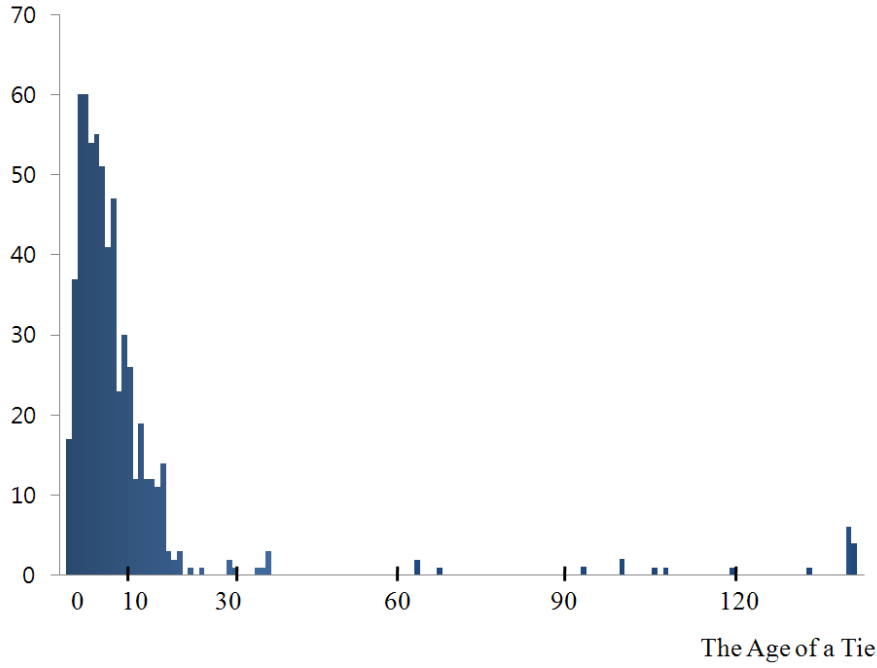
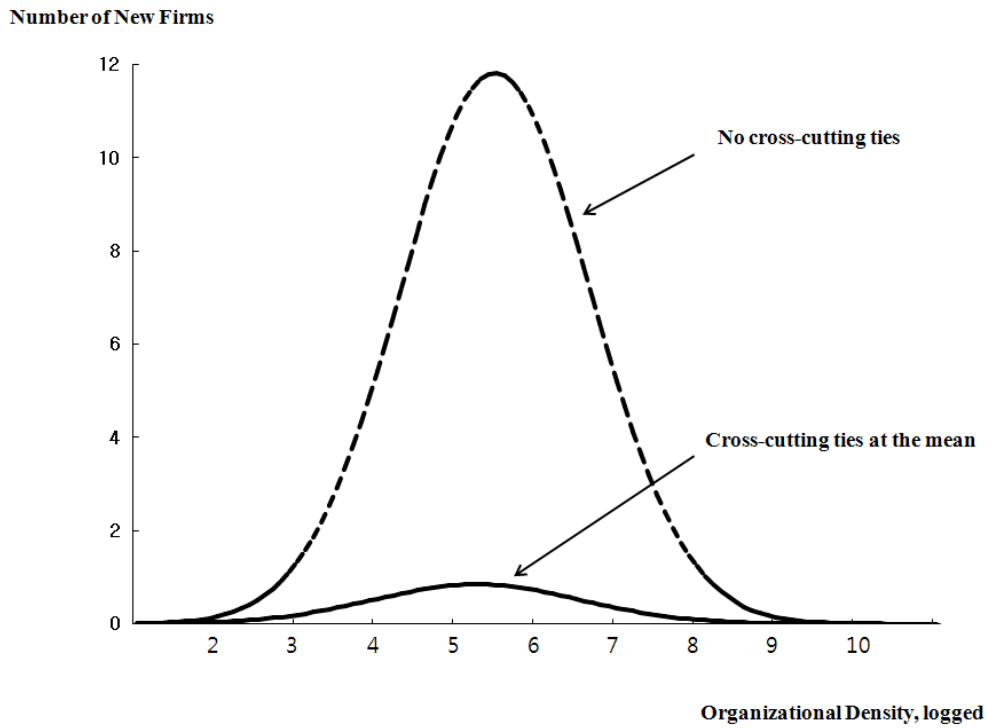


FIGURE 2. The Density Dependent Process Conditional upon Cross-Cutting Ties ¹⁾



1) The following equation is used to examine the interaction effects: $Y = \exp(-8.196 + 3.894 \cdot OD - 0.355 \cdot OD^2 - 0.148 \cdot OD \cdot CT + 0.011 \cdot OD^2 \cdot CT)$, where OD refers to organizational density and CT refers to cross-cutting ties.

TABLE 1
Means, Standard Deviations, and Pearson Correlations ^a

	Mean	S. D.	2	3	4	5	6	7	8
1. New firm formation	4.361	8.505	0.614	0.817	0.134	0.599	0.164	0.709	0.536
2. Organizational density, logged	4.490	1.152		0.614	0.449	0.406	0.302	0.764	0.474
3. Cross-cutting ties	5.607	13.23			0.110	0.653	0.166	0.652	0.449
4. Network constraint	0.319	0.352				0.061	0.145	0.269	0.127
5. Tie involving new firms	0.102	0.398					0.085	0.388	0.283
6. Venture capital per density	3.002	3.592						0.259	0.228
7. Number of S&E Depart. graduates	1.000	0.981							0.472
8. Sum of university R&D spending	2.807	6.459							

N = 244. All are significant at 0.05 significance level except the correlations of Tie involving new firms with Network constraint and Venture capital per density.

TABLE 2

The Unconditional Fixed Effects Poisson Model For Entries into the Industry

	Model 1	Model 2	Model 3	Model 4
Constant	-6.466 (3.663)	-8.196 (4.851)	-26.74 ** (6.732)	-9.753 * (4.465)
Venture capital per density	-0.003 (0.011)	-0.006 (0.012)	-0.015 (0.035)	-0.001 (0.012)
Number of S & E depart. graduates	-1.663 * (0.655)	-0.849 (0.781)	2.119 (1.126)	-1.150 (0.739)
Sum of university R&D spending	0.016 ** (0.006)	0.004 (0.009)	0.657 (0.909)	0.009 (0.007)
Organizational density, logged [<i>OD</i>]	3.608 ** (1.199)	3.894 * (1.683)	9.073 ** (2.369)	3.682 * (1.637)
<i>OD</i> ²	-0.331 ** (0.109)	-0.355 * (0.166)	-0.848 ** (0.231)	-0.312 (0.172)
Ties involving new firms	-0.146 * (0.072)	-0.175 * (0.079)	0.176 * (0.088)	-0.164 ** (0.074)
Network constraint	0.264 (0.172)	0.143 (0.179)	-0.334 (0.222)	0.185 (0.177)
Cross-cutting ties [<i>CT</i>]		0.476 * (0.244)	1.502 ** (0.385)	0.888 * (0.408)
<i>OD</i> x Cross-cutting ties		-0.148 * (0.071)	-0.448 ** (0.116)	-0.199 * (0.096)
<i>OD</i> ² x Cross-cutting ties		0.011 * (0.005)	0.033 ** (0.009)	0.014 * (0.006)
Year 1995	-0.258 * (0.121)	-0.290 * (0.130)		-0.285 * (0.122)
Year 1996	0.141 (0.177)	0.108 (0.178)	0.439 ** (0.136)	0.105 (0.179)
Year 1997	0.304 (0.209)	0.265 (0.211)	0.468 * (0.222)	0.252 (0.213)
Year 1998	0.161 (0.319)	0.307 (0.329)	0.512 (0.281)	0.209 (0.327)
Region specific effects	Included	Included	Included	Included
Number of observations	244	244	194	244
χ^2 (d.f) vs. Model 1		8.7 (3) *	18.6 (3) **	7.1 (3)

* p<.05; ** p<0.01 (two tailed tests); Standard errors are in parentheses. ML estimates are reported. All covariates are one-year lagged in Model 3. New firms at year T refer to de novo entries that did not exist prior to T. In Model 4, cross-cutting ties are instrumented by the number of inhabitants and venture capital per density.

TABLE 3
Alliance Type, Carrying Capacity and New Firm Formation

	Model 1	Model 2	Model 3	Model 4
Constant	-1.338 (3.432)	-8.631 (4.680)	-11.323 * (4.765)	0.226 (7.883)
Venture capital per density	-0.003 (0.011)	-0.008 (0.011)	-0.007 (0.013)	-0.008 (0.014)
Number of S & E depart. graduates	-1.537 * (0.740)	-0.866 (0.755)	-0.161 (0.842)	-0.206 (0.333)
Sum of university R&D spending	-0.002 (0.006)	0.006 (0.008)	0.007 (0.007)	0.114 (0.346)
Organizational density, logged [<i>OD</i>]	2.432 (1.727)	3.983 * (1.611)	4.836 ** (1.617)	6.978 (3.653)
<i>OD</i> ²	-0.302 (0.253)	-0.360 * (0.156)	-0.443 ** (0.160)	-7.120 * (2.806)
Ties involving new firms	-0.129 (0.075)	-0.152 * (0.076)	-0.209 * (0.092)	-0.335 * (0.156)
Network constraint	0.281 (0.171)	0.132 (0.178)	0.194 (0.176)	-0.024 (0.221)
Cross-cutting ties	0.412 * (0.183)	0.840 ** (0.292)	-0.137 (0.615)	0.086 * (0.036)
<i>OD</i> x Cross-cutting ties	-0.228 * (0.094)	-0.247 ** (0.086)	-0.028 (0.181)	-0.224 ** (0.083)
<i>OD</i> ² x Cross-cutting ties	0.031 * (0.012)	0.018 ** (0.006)	0.007 (0.013)	0.156 ** (0.058)
Year dummies	Included	Included	Included	Included
Region specific effects	Included	Included	Included	Included
Number of observations	244	244	244	135
χ^2 (d.f) vs. Intercept-only model	1794 (62)	1807 (62)	1809 (62)	508 (40)

* p<.05; ** p<0.01; Standard errors are in parentheses. ML estimates are reported. For Model 1, organizational density is divided by the number of inhabitants. For Models 2 and 3, cross-cutting ties are based on alliances that involve technology licensing agreements (427 cases) and those without licensing agreements (194 cases), respectively. The unit of analysis for Model 4 is the metropolitan area and cross-cutting ties in this model are based on alliances that involve technology licensing agreements. Note that organizational density is not log-transformed in Model 4.

TABLE 4
The Effects of Cross-Cutting Ties on Knowledge Diversity

	Model 1	Model 2
	Knowledge Diversity	Complementary-adjusted Knowledge Diversity
Constant	0.779 ** (0.024)	0.429 (1.144)
Venture capital per density ($\times 10^{-1}$)	0.003 (0.006)	0.509 (0.262)
Sum of university R&D spending ($\times 10^{-1}$)	-0.004 (0.005)	0.207 (0.216)
Number of S & E depart. Graduates ($\times 10^{-1}$)	0.094 ** (0.036)	-3.753 * (1.703)
Organizational density, logged (<i>OD</i>)	0.063 ** (0.012)	1.376 * (0.549)
<i>OD</i> ²	-0.008 ** (0.002)	-0.164 * (0.070)
Cross-cutting ties, logged ($\times 10^{-1}$)	0.064 * (0.029)	0.917 ** (0.139)
Year 1995	-0.002 (0.006)	0.200 (0.282)
Year 1996	-0.003 (0.006)	0.058 (0.282)
Year 1997	-0.006 (0.006)	0.659 * (0.283)
Year 1998	-0.015 (0.007)	0.270 (0.342)
σ of the latent dependent variable	0.029 ** (0.001)	1.378 ** (0.062)
Number of observations	244	244
χ^2 (d.f) vs. Intercept-only model	43.55 (10)	87.93 (10)

* p<.05; ** p<0.01 (two tailed tests); Standard errors are in parentheses. The ML estimates of the double censored Tobit model are reported.

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